Renewable and Sustainable Energy Reviews 16 (2012) 898–903

Contents lists available at SciVerse ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Performance assessment of Alternative Energy Resources in Brazilian power sector using Data Envelopment Analysis

Marcos Estellita Lins[a], Luciano Basto Oliveira[b], Angela Cristina Moreira da Silva[a], Luiz Pinguelli Rosa[c], Amaro Olimpio Pereira Jr.[d,*]

[a] Programa de Engenharia de Produção (PEP/COPPE/UFRJ), Brazil
[b] Instituto Virtual Internacional de Mudanças Globais (IVIG/COPPE/UFRJ), Brazil
[c] Programa de Planejamento Energético (PPE/COPPE/UFRJ), Brazil
[d] Centro de Estudos Integrados sobre Meio Ambiente e Mudanças Climáticas (CentroClima/COPPE/UFRJ), Caixa Postal 68565, CEP 21941-972, Ilha do Fundão, Rio de Janeiro, Brazil

ARTICLE INFO

Article history:
Received 23 December 2010
Received in revised form 15 August 2011
Accepted 7 September 2011
Available online 5 October 2011

Keywords:
Data Envelopment Analysis
Performance indicators
Alternative Energy Resources

ABSTRACT

The Brazilian power sector is known for the strong participation of renewable sources. This characteristic is maintained thanks to government incentives for alternative sources with particular emphasis on wind generation, small hydroelectric and sugar cane bagasse fired power plants, because these are more costly than conventional plants; they are, nevertheless, less costly than other alternative sources, such as residue-based generation. The government's policy is based, however, on a purely economic analysis. If socio-environmental variables were to be taken into account the government's orientation in favor of renewable sources might be different. The present article uses the Data Envelopment Analysis (DEA) method to incorporate such variables in the government's energy policies. The results demonstrate the advantage of promoting residue based generation above that from other sources.

Contents

1. Introduction

The Brazilian power sector is characterized by the strong presence of hydroelectric plants, with large reservoirs of pluri-annual regularization, situated in different hydrographic basins, and distant from the consumer centers. For this reason, extensive transmission lines are required, not only to transport the electricity generated to the consumers but also to integrate the systems to each geographic region. The hydraulic capacity is complemented by conventional thermal, nuclear and, more recently, wind power plants.

According to the 2008 National Energy Balance – BEN [1], Brazil had an installed power generation system with a capacity of about 104 GW, of which over 78 GW of hydropower, 23 GW of conventional thermal power plants, 2 GW of nuclear and 414 MW of wind farms.

This profile, however, can change greatly, depending on the growth of electricity demand and the availability of resources for the generation as well as the cost of exploitation of these resources.

While, on one hand, the country has a wide variety of natural resources, their exploitation, on the other, can result in major investments and significant environmental impacts. In any case, the country has demonstrated the intention of maintaining a big participation by renewable sources, going as far as to create incentive

* Corresponding author. Tel.: +55 21 2562 8774; fax: +55 21 2562 8777.
E-mail addresses: lins@pep.ufrj.br (M.E. Lins), luciano@ivig.coppe.ufrj.br (L.B. Oliveira), angela@pep.ufrj.br (A.C.M. da Silva), lpr@adc.coppe.ufrj.br (L.P. Rosa), amaro@ppe.ufrj.br (A.O. Pereira Jr.).

1364-0321/$ – see front matter
doi:10.1016/j.rser.2011.09.010

mechanisms for the promotion of such alternatives with emphasis on wind generation, small hydroelectric and sugar cane bagasse fired power plants. These technologies are not competitive with conventional ones, although they are cheaper than other alternative sources, such as residue-based generation.

The question of competitiveness between sources, however, is based on a purely economic analysis. If socio-environmental variables were to be taken into account government incentives might be directed at other sources.

Urban waste, for instance, has additional advantages normally not taking into account, such as: (i) the equipment and input materials required for its production are sourced in Brazil and thus priced in local currency; (ii) it is a labor-intensive option that requires screening and sorting, in order to separate out recyclable items from waste biomass; (iii) it is normally available close to consumers, resulting in lower electricity transmission costs and losses; and (iv) it helps reducing pollution through replacing fossil fuels by Alternative Energy Resources and avoiding the decomposition of solid wastes and GHG emissions.

These advantages may be assessed through an integrated and qualitative technical, social, economic and environmental analysis of the various effects of this use, through adequate methodology. Thus, the present study addresses the application of the Data Envelopment Analysis (DEA) method to a study of the performance of Alternative Energy Resources for the Brazilian power sector, in order to show the importance of this tool in the energy policy formulation.

2. Data Envelopment Analysis (DEA)

When the electricity generated by the Alternative Energy Resources is more expensive than that produced by traditional resources, meaning when the assessment criteria are only economic, the Alternative Energy Resources become feasible only where there is no supply based on traditional resources. However, there are social, environmental and technological aspects that are well able to justify a different approach to assessment, based on the concept of Sustainable Development.[1] To do so, methodologies able to handle multiple criteria must be used, while also considering input/output type relations [2]. In this paper, a quantitative method has been selected, based on linear programming: Data Envelopment Analysis (DEA), which is described below.

2.1. Basic concepts

Calculating the efficiency of organizational units has been an important topic for management, although hard to handle, particularly when multiple inputs (resources) and multiple outputs (services, products and others) are associated with these units. Proposed ways of addressing this problem are found in the paper by Farrell [3], from which an empirical relative efficiency frontier was derived, instead of a theoretical production function, used as basis for measuring the relative efficiency of the units.

Charnes et al. [4] created a technique based on linear programming for calculating the relative efficiency of the units, grounded on the proposal presented by Farrell [3], and established a point of reference on the frontier for each inefficient unit. They called their new approach to efficiency measurement: Data Envelopment Analysis (DEA) and the units under assessment were called Decision Making Units (DMUs).

[1] Integrated analysis of social, environmental, technical, operating and economic feasibilities, in order to ensure the development of today's populations without adversely affecting the living conditions of future generations, which is an attitude grounded on inter-generational accountability.

From the time it was developed through until today, Data Envelopment Analysis (DEA) has been used to study the relative efficiency of units in many areas, such as education, hospital administration, maintenance units in the US Air Force etc. In some cases, the solutions obtained through DEA result in efficiency ratings and marginal substitution rates that are hard to construe, meaning that they are often not accepted by managers. It should be noted that it is of the utmost importance to be familiar with the trade-offs (marginal substitution rates) between the inputs and outputs in a production process. For example, managers often need to know the additional amount of a certain input that is required to step up a specific output, while the remaining factors continue unchanged.

Through the DEA technique, trade-offs between inputs and outputs may be calculated under optimum operation conditions on the efficient frontier, through the ratio between the multiplicatory factors associated with each input/output pair, two inputs or two outputs. Thus, if u_1 and u_2 are the multiplicatory factors for output 1 and output 2 respectively obtained for a given DMU j, the u_1/u_2 coefficient will represent the amount by which output 2 of the DMU j must be increased in order to offset a reduction unit in the output 1 of the DMU j. Thus, the slants of the corresponding segments of the efficient frontier defined by the DEA technique represent the trade-offs between the inputs and outputs, although the calculation of the trade-offs obtained through the DEA multiplicatory factors presents some difficulties. In mathematical terms, the trade-offs represent the partial derivates on the frontier, meaning the angle of the production frontier at a specific point. The DEA technique builds up a linear frontier by parts, in order to approach the production frontier. The DEA frontier has the following constraints:

1. It is continuous, but at the points corresponding to the extremely efficient DMUs, the derivates are not continuous [4]. This fact means that the problem of the DEA multiplicatory agents, prepared to measure the efficiency of extremely efficient DMUs, has multiple optimum solutions.
2. The DEA frontier has efficient non-Pareto-efficient/Koopmans regions where there are no clearly defined marginal substitution rates because at least one of the multiplicatory agents determining the hyperplane equation characterizing this region has a value equal to zero. In DEA models with variable returns of scale, there will be an efficient DMU for each input and output (with the minimum value of an input or maximum value of an output). It is easy to show that each of these DMUs corresponds to a non-Pareto-efficiency region. In models with constant returns of scale, for each input/output pair, the DMU with the highest output/input relation will be efficient, determining the origin of a non-Pareto-efficiency region.

The main problem of the DEA models is not the existence of non-Pareto-efficiency regions, but rather the projection of inefficient DMUs in these regions. This occurs mainly because the classic DEA models assume radial spoke displacement projections, for the sake of simplicity. Alternative ways of dealing with this issue include weight restrictions [5], multi-objective models [6] or the use of artificial DMUs as proposed by Thanassoulis and Allen [7].

In this paper, we opted for the first alternative.

3. Preparation of the model

The units whose performance will be assessed are the Alternative Energy Resources for generating electricity, listed in the first column of Table 1. The criteria through which these decision units will be assessed are listed on the first line of this table.

It was decided to use a variable to deal with each of the dimensions of sustainability. Thus for the environmental dimension, gas

Table 1
Initial input and output data for the Alternative Energy Resources.

Alternative Energy Resources	Greenhouse Gases Emission (tCO_2/GW h)	Potential Job Creation (job/TW h)	Potential Distributed Power Generation (GW h/year)	O&M + CC Cost (US$/MW h)	Investment Cost (US$/MW h)
1. NGCC	452	7.21	83,220	52.00[a]	18
2. NGT	600	7.36	81,468	43.00[a]	27
3. Wind	–	14.27	17,520	7.00	43
4. Solar PV	–	6.12	49,056	4.00	76
5 SHPP	1	12.84	21,024	8.51	21.49
6. Rice Husks	−1223	43.90	6833	−3.28	24.98
7. GDL	−955	35,347.69	28,330	10.86	46.67
8 DRANCO	−263	14,430.86	69,587	−26.52	33.48
9. Incineration	−524	20,233.78	49,620	−4.71	62.63
10. CCO	−278	15,818.92	63,620	8.20	51.52
11. BIG/STIG	−53.57	1.88	133,296	62.53	14.96

Source: Oliveira [8].
Labels: NGCC (Natural Gas Combined Cycle); NGT (Natural Gas Turbine); Solar PV (Photovoltaic); SHPP (Small Hydro Power Plant); GDL (Garbage Gas + Conservation); DRANCO (Garbage Gas from Digesters + Conservation); Incineration (steam from garbage + conservation); CCO (Optimized Combined Cycle with Incineration); (BIG/STIG) Cane Bagasse + P&P.
[a] Calculated based on the July 2007 electrical sector auction, in which the price of R$ 140/MW h was of no interest to the natural gas powered Thermoelectric Power Stations. The O&M + CC cost was calculated as the difference between this value and the investment.

emissions responsible for greenhouse gases were used; for the social dimension, the number of jobs created; for the economic, the investment cost; for the operational, the operating and maintenance costs, plus fuel cost; for the strategic, the energy supply potential.

In order to use the above amounts in the Data Envelopment Analysis (DEA) it was necessary to alter the variables so as to avoid negative or nil values. To do so, all the cells in each column with negative or nil values were added to the lowest value in this column, with the addition of one unit. Thus, all the cells in the Greenhouse Gases Emissions column total were 1244.57, while the values in the O&M + CC Costs column were increased by 27.52. These changes do not affect the performance ranking, but only the indicator value.

Rows 7–10 represent the technological routes for turning waste into energy, enhancing power generation and conservation through recycling. At this point it is important to highlight the factors on which estimates were based: in the case of GDL recuperation the organic portion refers to 60% of MSW availability (55 Mt/y) and its conversion into electricity is 0.15 MW h/t, while the use of disposable recyclable materials (35%), whose energy saving factor is of 3 MW h/t, was of the order of 40%; in the case of Anaerobic Digestion the conversion factor is 0.5 MW h/t and the use of recyclables reaches 90%. In incineration and CCO recycling is reduced, due to the need for part of this material to be used to add calorific value to the organic fraction. In incineration, where the electricity generation factor reaches 0.7 MW h/t, 85% of the MSW was used and recyclable represent 10% of the MSW, while in CCO, generation factor reaches 0.9 MW h/t, 80% of MSW was used for generation and 15% for recycling.

Rows 8–10, the waste gas route is compatibilized with the others, as landfill gases may be tapped regardless of the technological route used for the new garbage.

As Data Envelopment Analysis (DEA) allows the variables to be classified as inputs or outputs, those selected in compliance with the Sustainable Development concept were:

- Inputs: number of jobs generated, potential electricity provided, and Greenhouse Gases Emissions;
- Outputs: investment cost and operations and maintenance costs.

It is noted that Greenhouse Gases Emissions constitute an undesirable output. The undesirable outputs may be included in DEA models through four main approaches. The first uses an inverse transformation, according to Golany and Roll [9]; Scheel [10], and Lovell et al. [11]. The second considers the output as an input, according to Omo, in Rheinhard et al. [12], Scheel [10]. The third proposes to reverse the output signal and add a positive scalar, valid only for the DEA BCC models [13] and Additive [4], as the CCR is not invariant for translation. The fourth option, proposed by Färe and Grosskopf [14,15], consists of considering the congestion hypothesis on the undesirable output, with no need to maintain the output level when some input increases. However, Dyckhoff and Allen [16] stress that this proposal should only be used if the decision-taker is certain of the technical links between the undesirable output and known inputs and outputs.

In this paper, we decided to consider the undesirable output as a proxy for a depletable environmental resource, representing this as an input.

Table 2
Input and output entry data.

Alternative Energy Resources	Inputs			Outputs	
	Greenhouse Gases Emission (tCO_2/GW h)	Potential Job Creation (job/TW h)	Potential Distributed Generation (GW h/year)	O&M + CC Cost (US$/MW h)	Investment Cost (US$/MW h)
1. NGCC	1676.57	600	83,220	79.52	18.00
2. NGT	1824.57	600	81,468	70.52	27.00
3. Wind	1224.57	250	17,520	34.52	43.00
4. Solar PV	1224.57	300	49,056	31.52	76.00
5 SHPP	1225.57	270	21,024	36.03	21.49
6. Rice Husks	1.00	300	6833	24.24	24.98
7. GDL	269.29	1,001,400	28,330	38.38	46.67
8 DRANCO	961.43	1,004,200	69,587	1.00	33.48
9. Incineration	699.84	1,004,000	49,620	22.81	62.63
10. CCO	946.35	1,006,400	63,620	35.72	51.52
11. BIG/STIG	1171.00	250	133,296	90.05	14.96

Source: Prepared by the authors.

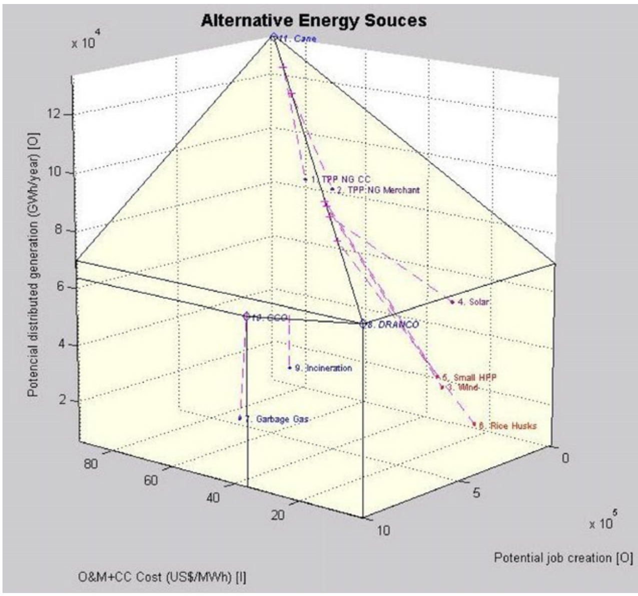

Fig. 1. O&M + CC Cost versus Potential Job Creation and Potential Distributed Generation. *Labels*: UTE GN CC (NGCC); UTE GN Merchant (NGT); Solar (Solar PV).

The two last columns of Table 2 represent the outputs (O), while the other three represent the inputs (I). The model logic is to assign priority to the lowest input and the highest output.

3.1. Preliminary graph analysis

Three-dimensional graph analysis may be important for helping construe the findings produced by the complete model. This is possible through the development of the Interactive Data Envelopment Analysis (IDEAL) software at COPPE. It is important to note that the DMUs shown as efficient in the partial graph analyses will also be so in the full classic model. However, as noted, we will use

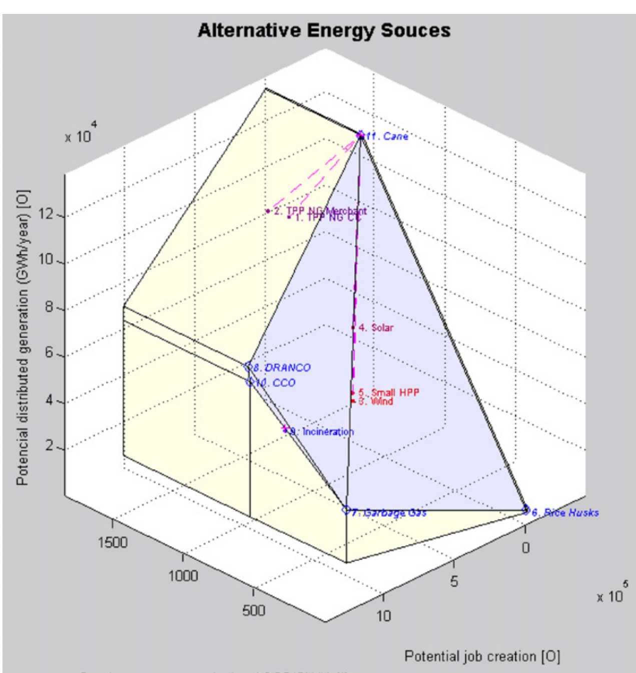

Fig. 2. Greenhouse Gases Emission versus Potential Distributed Generation and Job Creation. *Labels*: UTE GN CC (NGCC); UTE GN Merchant (NGT); Solar (Solar PV).

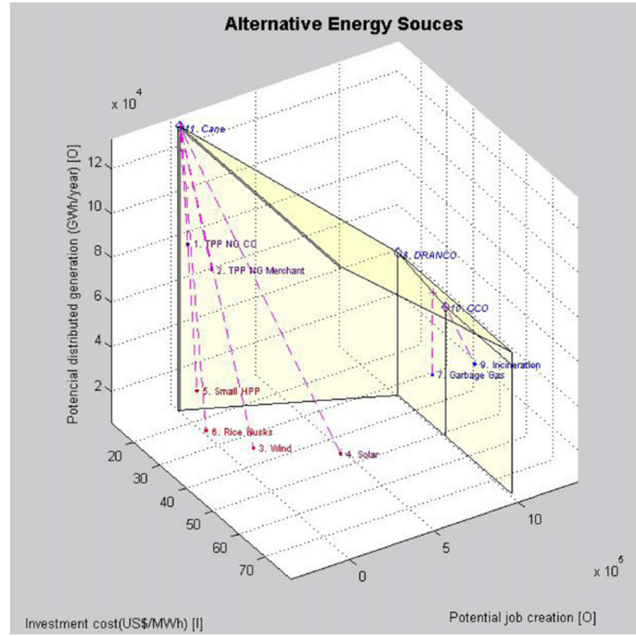

Fig. 3. Investment Cost versus Potential Job Creation and Energy Generation. *Labels*: UTE GN CC (NGCC); UTE GN Merchant (NGT); Solar (Solar PV).

model with constraints on the weights in order to avoid the Pareto-inefficient regions and adapt the weight to the specialist's opinion. The graph analysis presented below:

The first graph in Fig. 1 shows a Pareto-efficiency face and a peak when considering the "O&M Cost Variables" (input), "Distributed Generation" (output) and "Job Creation" (output). Three alternative efficient resources are shown (CCO, Dranco and bagasse + P&P, BIG/STG) which constitute only two Pareto efficient frames. It must be pointed out that DRANCO presents the most stable situation in the DMU assembly.

The second set of variables analyzed corresponds to the "Energy Generation", "Job Creation" and "Greenhouse Gases Emissions" outputs, shown in Fig. 2. It is noted that the efficient frontier consists of three faces: one defined by the "Garbage Gas", "DRANCO" and "cane bagasse + P&R (BIG/STIG)" DMUs, other by "Garbage Gas", "CCO" and "DRANCO" and the last by "Garbage Gas", "Cane Bagasse + P&P (BIG/STIG)" and "Rice Husks".

The third set of variables, consisting of "Investment", "Job Creation" and "Energy Generation", is shown in Fig. 3. In this case, we have only two frames, one constituted by the sugar cane bagasse P&P (BIG/STIG) technology and the other by "CCO".

3.2. Constraints on weights

Wong and Beasley [17] explore the use of constraints on virtual inputs/outputs, defined as the product of the input value by the weight assigned to it in the DEA multiplicatory agent model. The proportion of the total virtual of the DMU *j* may be curtailed, used by the output *r*, i.e., the "importance" of output *r* by DMU *j* at the

Table 3
Limits assigned to constraints on input and output weights.

Inputs and outputs	Lower	Upper
Potential Distributed Generation (GW h/year)	0.4	0.6
Potential Job Creation (job/TW h)	0.4	0.6
Greenhouse Gases Emission (tCO_2/GW h)	0.3	0.5
Investment Costs (US$/MW h)	0.3	0.5
O&M + Fuel Costs	0.3	0.5

Source: Authors based on Wong and Beasley's [17] methodology.

Table 4
Findings for the model with constraints on the virtual weights.

Alternative Energy Resources	Efficiency	Virtual weights				
		Inputs			Outputs	
		Greenhouse Gases Emission (tCO_2/GW h)	O&M + CC Cost (US$/MW h)	Investment Cost (US$/MW h)	Potential Job Creation (job/TW h)	Potential Distributed Generation (GW h/year)
1. NGCC	0.65	0.30	0.40	0.30	0.60	0.40
2. NGOC	0.47	0.30	0.40	0.30	0.60	0.40
3. Wind	0.46	0.30	0.30	0.40	0.60	0.40
4. Solar PV	0.39	0.32	0.30	0.38	0.50	0.50
5 SHPP	0.67	0.30	0.40	0.30	0.60	0.40
6. Rice Husks	1.00	0.30	0.30	0.40	0.60	0.40
7. GDL	1.00	0.40	0.30	0.30	0.59	0.41
8 DRANCO	1.00	0.30	0.40	0.30	0.50	0.50
9. Incineration	0.68	0.40	0.30	0.30	0.40	0.60
10. CCO	0.60	0.40	0.30	0.30	0.40	0.60
11. BIG/STIG	0.75	0.30	0.40	0.30	0.60	0.40

interval between $[\phi_r, \psi_r]$, with ϕ_r and ψ_r being determined by the decision-taker or user. Thus, the constraint on virtual output r is presented below:

$$\phi_r \le \frac{u_r y_{rj}}{\sum_{r=1}^{s} u_r y_{rj}} \le \psi_r \tag{1}$$

where $\sum_{r=1}^{s} u_r y_{rj}$ represents the total virtual output of the DMU j. A similar constraint may be imposed on virtual inputs.

There are some alternatives for implementing this type of constraint, stressing the following, suggested by Wong and Beasley [17]:

- Impose the constraint only on the DMU under assessment, thus, each DMU is analyzed with two additional constraints. The inconvenient aspect of this approach is that a benchmark DMU may not always need to be efficient, in turn.
- Add this constraint to all the DMUs. Thus, each DMU is assessed with $2N$ additional constraints, with N being the total number of DMUs. This procedure results in frequent blocks in the linear programming problem, as stressed by Lins et al. [18].

Variables are used with associated weightings in DEA methodology. The ideal for restrictive application is that these should be the result of opinion research of specialists, following the establishing of a sampling plan. When this is not applicable, the narrowest range of each variable can be estimated by means of simulation, the alternative applied in the present study. Thus, in order to apply the DEA model and ensure its feasibility, we decided to impose constraints on the virtual inputs and outputs only for the DMU under analysis. The acceptable range is presented in Table 3.

The findings obtained with virtual weights are presented in Table 4.

The findings show that three technologies tie for first place: “Rice Husks” and two garbage-based options: “Garbage Gas” and “DRANCO”. Of these only the “DRANCO” presents a performance indicator with maximum value in the three partial analysis graphs of item 3.3 which used classical models. It is noted that “GDL” and “Rice Husk” technologies showed themselves efficient in partial analyses only when greenhouse gases were considered as input.

The “Bagasse + P&P (BIG/STIG)” and “CCO” technologies, apart from being found efficient in all the partial analyses made without restriction to averages, only reached the fourth and eighth ranking respectively in the analysis using restriction to averages and under the imposed limits, as presented in Table 3.

The application of the benchmark concept allows the tied alternatives to be ranked. Table 5 presents this ranking by Data Envelopment Analysis (DEA) for the Alternative Energy Resources.

Table 5
Alternative Energy Resources ranking by hierarchical options.

Alternative Energy Resources	Ranking		
	Without conservation	With conservation	With conservation and DEA model
1. NGCC	7	8	7
2. NGOC	8	9	9
3. Wind	3	4	10
4. Solar PV	10	11	11
5 SHPP	2	3	6
6. Rice Husks	1	2	3
7. GDL	5	5	2
8 DRANCO	4	1	1
9. Incineration	11	6	5
10. CCO	6	7	8
11. BIG/STIG	9	10	4

In comparing the result of hierarchisation based exclusively on Cost Benefit Indexation and without considering the conservation of energy provided by recycling, it can be verified that the alternatives for energy recovery from urban waste, when energy conservation resulting from recycling is not taken into account, do not figure among the best three – occupying the 4th, 5th, 6th and 11th positions. This analysis is consistent with investment factors typical of this sector and with the levels of generation efficiency found in each technology currently in vogue.

Once the conservation for each alternative is taken into account the results change; that which was in 4th position becomes the best alternative while the rest remain 5th (same as in the first hierarchy), 6th (previously 11th) and 7th (previously 6th). This leads to the conclusion that the effect of conservation is very significant in technologies for energy recovery from urban waste, although this is not the case with the Optimized Combined Cycle – a technological alternative where increase in investment and conservation are not significant when compared with that of incineration.

Once energy conservation resulting from recycling is taken into account in the multicriterion analysis represented by the DEA model, the hierarchy remains in first place, the 5th placed technology becomes 2nd, the 6th placed becomes 6th, but that which was in 7th place goes down to 8th.

4. Conclusion

Renewable Energy Resources are starting to play an important role in electricity supplies again, after having lost out to mineral resources, except in Brazil. The advantages offered by large-scale power plants have proved insufficient, when assessed

on the basis of broad-ranging assumptions, taking into consideration factors that are not measurable solely in economic terms, such as Job Creation, pollutant emission control and system safety.

However, traditional decision-making support tools are not yet adapted to display the advantages of renewable energy resources, with only a few successful cases being known, such as Brazil's hydro-power plants that account for over 73% of electricity generated nationwide, but with an installed capacity similar to that of the USA, which reaches only 30%.

In order to take into consideration the variables most relevant to renewable energy resources, without neglecting those usually assessed for traditional energy resources, the Sustainable Development Concept was used, which consists of complying with environmental, social, economic, technological and operating requirements.

The application of this concept involves multiple criteria and requires a methodology that can assess the efficiency of production units based on multiple inputs and outputs. To do so, the Data Envelopment Analysis (DEA) technique was selected, based on linear programming, in order to calculate the relative efficiency of the units, represented by drawing up an efficiency frontier. This methodology can determine a reference point on the frontier for each inefficient unit, taking into account each of the aspects under analysis, based on a range of variations assigned by a specialist or the decision-taker.

As Data Envelopment Analysis (DEA) requires the definition of groups of input and output variables, those selected in compliance with the Sustainable Development Concept were divided up as follows:

- Inputs: investment cost and operations and maintenance costs;
- Outputs: number of jobs generated, potential electricity provided, and Greenhouse Gases Emissions.

The findings show that technologies using solid wastes to generate energy should be assigned higher priority than the other options analyzed, including those fueled by natural gas and other renewable energy resources.

These findings are important to assist decision taking at various levels of government on this matter, as the option for distributed power generation using renewable resources based on solid wastes may well cover 30% of consumption nationwide at competitive prices, lessening pollution and offering jobs to poorly skilled workers.

This justifies a government policy stipulating exclusive service through technologies making good use of solid urban wastes, for a minimum period to be defined, of a portion of the price to be stipulated by the Ministry of Mines and Energy (MME) for renewable energy resources, in order to encourage the fine-tuning of equipment production that will result in gains of scale and optimized processes.

References

[1] EPE – Empresa de Pesquisa Energética. Balanço Energético Nacional – Ano Base 2008. Brasil/Ministério de Minas e Energia – MME; 2009.
[2] La Rovere EL, Soares JB, Oliveira LB, Lauria T. Sustainable expansion of electricity sector: sustainability indicators as an instrument to support decision making. Renewable and Sustainable Energy Reviews 2010;14:422–9.
[3] Farrell MJ. The measurement of productive efficiency. Journal of the Royal Statistical Society, Serialize THE, General 1957;3:253–81.
[4] Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision-making units. European Journal of Operational Research 1978;2(6):429–44.
[5] Pedraja-Chapparo R, Salinas-Jimenez J, Smith P. On the role of weight restrictions in Data Envelopment Analysis. Journal of Productivity Analysis 1997;8:215–30.
[6] Lins MPE, Meza LA, Silva ACM. A multi-objective approach to determine alternative targets in Data Envelopment Analysis. Journal of the Operational Research Society 2004;55:1090–101.
[7] Thanassoulis E, Allen R. Simulating weight restrictions in Data Envelopment Analysis by means of unobserved DMUs. Management Science 1998;44:586–94.
[8] Oliveira LB. Potencial de aproveitamento energético de lixo e de biodiesel de insumos residuais no Brasil. D.Sc. thesis. Energy Planning Program. COPPE/UFRJ; 2004. p. 237.
[9] Golany B, Roll Y. An application procedure for DEA. Omega – The International Journal of Management Science 1989;17:237–50.
[10] Scheel H. Undesirable outputs in efficiency evaluations. European Journal of Operational Research 2001;32:400–10.
[11] Lovell CAK, Pastor JT, Turner JA. Measuring macroeconomic performance in the OECD: a comparison of European and non-European countries. European Journal of Operational Research 1995;87(3):507–18.
[12] Rheinhard S, Lovell CAK, Thijssen G. Environmental efficiency with multiple environmentally detrimental variables estimated with SFA and DEA. European Journal of Operational Research 2000;121:287–303.
[13] Banker RD, Charnes A, Cooper WW. Some models to estimate technical and scale inefficiencies in Data Envelopment Analysis. Management Science 1984;30(9):1078–92.
[14] Färe R, Grosskopf S. Environmental decision models with joint outputs. Economics working paper archive, Economic Department, Washington University, US; 1995.
[15] Färe R, Grosskopf S. Optimization models applied to productivity and the environment. In: XXXIII Simpósio Brasileiro de Pesquisa Operacional. 2001.
[16] Dyckhoff H, Allen K. Measuring ecological efficiency with data envelopment analysis (DEA). European Journal of Operational Research 2001;132(2):312–25.
[17] Wong YHB, Beasley JE. Restricting weight flexibility in data envelopment analysis. Journal of the Operational Research Society 1990;41(9):829–35.
[18] Lins MPE, Silva ACM, Lovell CAK. Avoiding infeasibility in DEA models with weight restrictions. European Journal of Operational Research 2007;181(2):956–66.